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Sensitivity, Persistence and Asymmetric Effects in International Stock Market Volatility during the Global Financial Crisis

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ABSTRACT

Financial market volatility is an important element when setting up portfolio management strategies, option pricing and market regulation. The Subprime crisis affected all markets around the world.

Daily data of twelve stock indexes for the period of October 1999 to June 2011 are studied using basic GARCH type models. The data were then divided into three different sub-periods to allow the behavior of stock market in different sub-periods to be investigated. The following sub-periods are identified: Dot-Com crisis, Quiet and Subprime crisis. This paper revealed that the Subprime crisis turned out to have bigger impact on stock market volatility, namely at sensitivity, persistence and asymmetric effects.

Keywords: global financial crisis; international stock markets; GARCH models; conditional volatility.
JEL classification: G01; G15.
MSC2010: 91G80; 62M10; 62P20.

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Efectos de sensibilidad, persistencia y asimetría en la volatilidad de los mercados bursátiles internacionales en el entorno de la crisis financiera global

RESUMEN

La volatilidad de los mercados financieros es un importante elemento para la estrategia de carteras de inversión y para la regulación de los mercados. La crisis *subprime* afectó a los mercados bursátiles mundiales.

Para realizar este estudio, fueron tomados datos diarios relativos a doce mercados bursátiles, desde el 4 de octubre de 1999 hasta el 30 de junio de 2011. El período de la muestra considerado ha sido subdividido en tres subperíodos distintos: crisis de las empresas tecnológicas, tranquilo y crisis financiera global. Para estudiar la volatilidad de los mercados bursátiles, se ha recurrido a modelos de tipo GARCH.

Los resultados demuestran la influencia de la crisis financiera global en el comportamiento de la volatilidad del mercado bursátil, sobre todo en cuanto a la sensibilidad, la persistencia y la asimetría.

Palabras clave: crisis financiera global; mercados bursátiles; modelos GARCH; volatilidad condicional.
Clasificación JEL: G01; G15.
MSC2010: 91G80; 62M10; 62P20.

1. INTRODUCTION

According to Claessens *et al.* (2010), Bekaert *et al.* (2011) and Lin and Treichel (2012), the current financial crisis is the first global crisis and the most severe since the Great Depression. Although the crisis had its origin in the United States, particularly in subprime credit, it would be transmitted to other economic sectors as well as other developed and emerging economies.

The quantification of risk, as a financial variable, has represented a major challenge for researchers, regulators and financial professionals. In modern finance theory, Markowitz (1952) considers the volatility of asset's returns as a measure of risk. According to Lin (1996), the risk is usually associated with volatility. When the volatility of a financial asset rises, so does the risk. However, volatility measures only the magnitude, but not the direction. The financial markets volatility is an important indicator of the dynamic fluctuations in asset prices (Raja and Selvam, 2011). Understanding stock markets volatility is also an important element to calculate the cost of capital and to support investment decisions. Volatility is synonymous with risk. Bollerslev *et al.* (1992) argue that volatility is a key variable for a large majority of financial instruments, playing a central role in many areas of finance. Bala and Premaratne (2003) consider that substantial changes in financial market volatility can cause significant negative effects on risk aversion, and make markets more unstable, increasing the uncertainty for market players, particularly in their predictions and their income.

Usually, financial series reveal some enigmatic empirical regularity. These regularities are called stylized facts and correspond to observations so consistent, confirmed in many contexts, markets and instruments, which are eventually accepted as truth (Cont, 2001 and 2005). Thus, the stylized facts are based on a common denominator, which results from the properties observed in multiple studies, about markets and instruments. Due to its general nature, the stylized facts reveal a qualitative dimension, but not accurate enough to distinguish between different parametric models (Coolen, 2004; Ding *et al.*, 1993). Several studies have confirmed some of the most common stylized facts, including volatility clustering and asymmetric effect (Brock and de Lima, 1996; Campbell *et al.*, 1996; Mandelbrot and Hudson, 2006). The first is related to autocorrelation. According to Mandelbrot (1963) and Engle (1982), if volatility is high at a given moment, it tends to continue high in the next period. If volatility is low in a given moment, it tends to continue low in the next periods, because the new information that arrives to the market is correlated in time. For its part, the asymmetric effect results from the diverse reaction of volatility to the arrival of news in the market, reflecting the effect of good and bad news on volatility, which results in a negative correlation between lagged returns and volatility. The asymmetric effect was first observed by Black (1976).

Numerous studies have investigated daily volatility, particularly volatility clustering and asymmetric effect, using autoregressive conditional heteroskedasticity models (Schwert, 1998; Chaudhuri and Klaassen, 2001; Patev and Kanaryan, 2003; Ramlall, 2010; Chong, 2011; Angabini and Wasiuzzaman, 2011).

In this work conditional heteroskedasticity models are applied, in order to analyze the impact of global financial crisis on conditional volatility, sensitivity, persistence and asymmetric effect in the international stock markets.

This study is structured as follows: Section 2 presents information about the data and the methodology chosen, Section 3 shows the empirical results, while Section 4 summarizes the main conclusions.

2. DATA AND METHODOLOGY

In order to analyze the evolution of daily volatility stock markets, twelve indices were selected, evolving European, non-European, developed and emerging indices, according to the Morgan Stanley Capital International classification, representing about 62% of world stock market capitalization, in 2010, as can be seen in Table 1. The set of developed markets included European and non-european markets. From the European continent, Germany (DAX 30), France (CAC 40), UK (FTSE 100), Spain (IBEX 35), Ireland (ISEQ Overall), Greece (ATG) and Portugal (PSI 20) were selected. The set of non-European developed markets included the U.S. (Dow Jones), Japan (Nikkei 225) and Hong Kong (Hang-Seng). Additionally, Brazil (Bovespa) and India (Sensex) were selected as emerging stock markets.

We believe that the use of a large set of stock market indexes (emerging and developed), in different regions, with different capitalization levels, including some of the major stock markets of the world and the European markets under sovereign debt support program, it helps to understand the consequences of the global financial crisis.

Table 1: Market capitalization as a percentage of global capitalization

USA	UK	France	Japan	Spain	Brazil	Germany	Portugal	Greece	Hong-Kong	Índia	Ireland
30,5	5,5	3,4	7,3	2,1	2,8	2,5	0,1	0,1	4,8	2,9	0,06

Source: World Bank

The data used in this study were obtained from EconoStats and cover the period from October 4th 1999 to June 30th 2011, which was subdivided into three sub-periods. To analyze the Dot-Com crisis, the period from 10/04/1999 to 03/31/2003 was considered. The latest episode of crisis, which began in the U.S. with the subprime credit, considered the day of 08/01/2007 as the beginning of the crisis. For many authors, including Horta *et al.* (2008), Toussaint (2008) and Liquane *et al.* (2010), this day marked the beginning of subprime crisis, as a result of the rising rates of Credit Default Swaps. In addition to the sub-periods of crisis, a third sub-period was still considered, designated as quiet sub-period, from 04/01/2003 to 07/31/2007, corresponding to a general increase of global stock indices.

The time series in the level form were transformed into series of returns through the application of the expression $\ln(P_t/P_{t-1})$, where P_t and P_{t-1} represent the closing values of a particular index in days t and $t-1$, respectively.

To estimate the conditional volatility, GARCH (1,1) and EGARCH (1,1) models were considered. GARCH models were proposed by Bollerslev (1986) and they are consistent with the phenomenon of volatility clustering.

The GARCH (p, q) specification is given by:

$$y_{\mathrm{t}} = \varphi z_t + \varepsilon_t \tag{1}$$

$$\varepsilon_{\mathrm{t}} = \sigma_t \mu_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{3}$$

$$\alpha_j \geq 0\left(\forall_j = 1,\ldots,q\right); \tag{4}$$

where:

$\alpha_0 > 0$; $\alpha_j \geq 0\left(\forall_j = 1,\ldots,q\right)$; $\beta_i \geq 0\left(\forall_i = 1,\ldots,p\right)$; $\sum_{j=1}^{q}\alpha_j + \sum_{i=1}^{p}\beta_i < 1$ $\mu_t \sim N(0,1)$; $Cov(\mu_t;\varepsilon_{t-i}) = 0$; $\langle \varepsilon_{\mathrm{t}} | \tau_{t-1} \rangle \cap N\left(0,\sigma_t^2\right)$; $\tau_{t-1} = \{\varepsilon_{t-1}, \varepsilon_{t-2},\ldots\}$ is the set of the available information at time $t-1$, z_{t} is a vector of explanatory variables, q is the order of the ARCH process and p is the order of the GARCH process, ε_{t} corresponds to the vector of estimated residuals; α_{j} represents the short-term persistence shocks (ARCH effect) and β_{i} represents the long-term persistence shocks. $c_0 > 0$, $\alpha_j \geq 0\left(\forall_j = 1,\ldots,\boldsymbol{q}\right)$ and $\beta_i \geq 0\left(\forall_i = 1,\ldots,\boldsymbol{p}\right)$ are the basic conditions for the conditional variance to be positive $\left(\sigma_t^2 > 0\right)$.

The expression $\sum_{j=1}^{q}\alpha_j + \sum_{i=1}^{p}\beta_i < 1$ is the stationarity condition of the GARCH models. Verifying this condition ensures that conditional variance is not finite, while the conditional volatility varies in time, being positive and stationary. According to Alexander (2008), in a GARCH (1,1) model, the α_1 parameter measures the conditional volatility reaction to unexpected market shocks. When this parameter is relatively high (above 0.1), volatility is very sensitive to market events. The volatility persistence is considered usually as the sum of α_1 and β parameters. An alternative measure to evaluate persistence is volatility half-life. Engle and Patton (2001) define half-life as the median time spent by volatility to move halfway, back to its unconditional mean. This parameter provides a more appropriate description of persistence, representing the longest period in which the market shock will die. In a GARCH model, the half-life market shock is given by $\ln(0{,}5)/\ln(\alpha_1 + \beta)$.

To accommodate the asymmetric effect, Nelson (1991) proposed the EGARCH model, also called exponential GARCH. In this model, the conditional variance is described by an asymmetric function of past values of ε_{t}.

The EGARCH (p, q) model specification is given by:

$$y_{\mathrm{t}} = \varphi z_t + \varepsilon_t \tag{5}$$

$$\varepsilon_{\mathrm{t}} = \sigma_t \mu_t \tag{6}$$

$$\log(\sigma_t^2) = c_0 + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) \tag{7}$$

where:

γ_{k} measures the asymmetric effect; $\mu_t \sim N(0,1)$; $Cov(\mu_t;\varepsilon_{t-i}) = 0$; $\langle \varepsilon_{\mathrm{t}} | \tau_{t-1} \rangle \cap N(0,\sigma_t^2)$; $\tau_{t-1} = \{\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\}$ is the set of information available at the time $t-1$, z_{t} is a vector of explanatory variables, q is the order of the ARCH process and p is the order of the GARCH process, ε_{t} is the vector of estimated residuals. According to (McAleer, 2005), if $|\beta_1| < 1$, the conditional variance is finite.

As stated above, in the EGARCH (1,1) model, the asymmetric effect is captured by coefficient γ. The negative sign of this coefficient indicates the existence of an asymmetric effect; that is, it indicates a negative relationship between return and volatility. When the coefficient is negative, the positive shocks produce less pronounced volatility than negative shocks of equal size. This has been detected in several empirical studies, concluding that small investors are panicking about the impact of negative shocks and leave their market positions in order to avoid more pronounced losses. Consequently, there is an increase in volatility.

To verify the correct specification of the estimated models, the Ljung-Box and ARCH-LM tests were performed. Under the null hypothesis, $H_0 : \rho_1 = (\varepsilon_t^2) = \cdots = \rho_m = (\varepsilon_t^2) = 0$, the Ljung-Box test assumes that quadratic residues are not correlated. $\rho_i = (\varepsilon_t^2)$ concerns the correlation coefficient between ε_t^2 and ε_{t-i}^2. $\varepsilon_t^2 = u_t^2 / \sigma_t^2$ concerns the standardized quadratic residues. The Ljung-Box statistic is given by $Q = n(n+2)\sum_{i=1}^{m}\frac{\hat{\rho}_i^2(\hat{\varepsilon}_t^2)}{n-i} \sim \chi^2_{(m-k)}$, where k represents the number of estimated parameters.

The ARCH-LM test is considered under the null hypothesis $H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_q$, where q is the order of the process. The test statistic is given by NR^2, following an asymptotic distribution of χ^2, with q degrees of freedom, where R^2 is the determination coefficient and N the number of observations.

To conclude if stock markets volatility has increased, two types of tests are applied. The first involves the equality of means, using the t-test and the analysis of variance with one factor; the second test, the equality of variances by applying the F statistic and the Bartlett test. These tests are presented briefly below.

Tests for equality of means

The t-test is calculated based on

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^2} \tag{8}$$

The test is compared with Student-t distribution, where the number of degrees of freedom is given by:

$$v = \left\{ \frac{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^2}{\frac{S_1^2}{n_1^2(n_1-1)} + \frac{S_2^2}{n_2^2(n_2-1)}} \right\} \tag{9}$$

The test for equality of means, by analysis of variance with one factor, allows to evaluate the statistical significance of the difference between means, for a specific probability level, involving the calculation of the F statistic, which is based on the variability within and among sub-periods.

The test statistic is given by:

$$F = \frac{MSE}{MSD}$$

where:

$MSE = \frac{SSE}{k-1}$: is the average sum of squares between sub-periods;

$$MSD = \frac{SSD}{N-k}$$: is the average sum of squares within sub-periods.

whereas ***SSE*** is the sum of squares between sub-periods, ***SSD*** is the sum of squares within sub-periods, k is the number of sub-periods and N is the total number of observations.

In both tests, the null hypotheses and alternative hypotheses are:

$$H_{01} : \mu_{GFC} = \mu_{Dot-Com} \text{ and } H_{02} : \mu_{GFC} = \mu_{Quiet}$$

$$H_{a1} : \mu_{GFC} \neq \mu_{Dot-Com} \text{ and } H_{a2} : \mu_{GFC} \neq \mu_{Quiet}$$

Test for equal variances

The F test for equality of variances is given by

$$F = \frac{S^2_{higher}}{S^2_{lower}} \sim F_{T_{higher}-1;T_{lower}-1},$$

where $S^2_{higher(lower)}$ is the estimated variance of the sub-period with higher (lower) value.

The Bartlett's test is used to test equality/homogeneity of variances among groups versus the alternative of variances being unequal, for at least two groups.

The test statistic is given by:

$$2 = 2{,}3026 \times \left(\frac{q}{c}\right) \quad (10)$$

where:

$$q = (N-k)\log_{10} S^2_p - \sum_i^k (n_i - 1)\log_{10} S^2_i \quad (11)$$

$$c = 1 + \frac{1}{3(k-1)}\left[\sum_{i=1}^k (n_i - 1)^{-1} - (N-k)^{-1}\right] \quad (12)$$

$$S^2_p = \frac{\sum_{i=1}^k (n_i - 1)S^2_i}{N-k} \quad (13)$$

where n_i is the sample size of the *p*-th group, S^2_i is the sample variance of the *p*-th group, N is the sample size and S^2_p is the pooled variance.

In both tests, the null hypotheses and the alternative hypotheses are:

$$H_{01} : \mu_{GFC} = \mu_{Dot-Com} \text{ and } H_{02} : \mu_{GFC} = \mu_{Quiet}$$

$$H_{a1} : \mu_{GFC} \neq \mu_{Dot-Com} \text{ and } H_{a2} : \mu_{GFC} \neq \mu_{Quiet}$$

3. EMPIRICAL RESULTS

Figure 1 shows the daily returns series in the full period. The visual analysis indicates the tendency for volatility clustering in certain periods. The second sub-period was relatively quiet. However, the remaining sub-periods showed great turbulence and volatility, suggesting volatility clustering, as we will see later on. The year of 2008 revealed the highest volatility concentration as the result of the emergence of the global financial crisis.

Figure 1. Evolution of daily returns

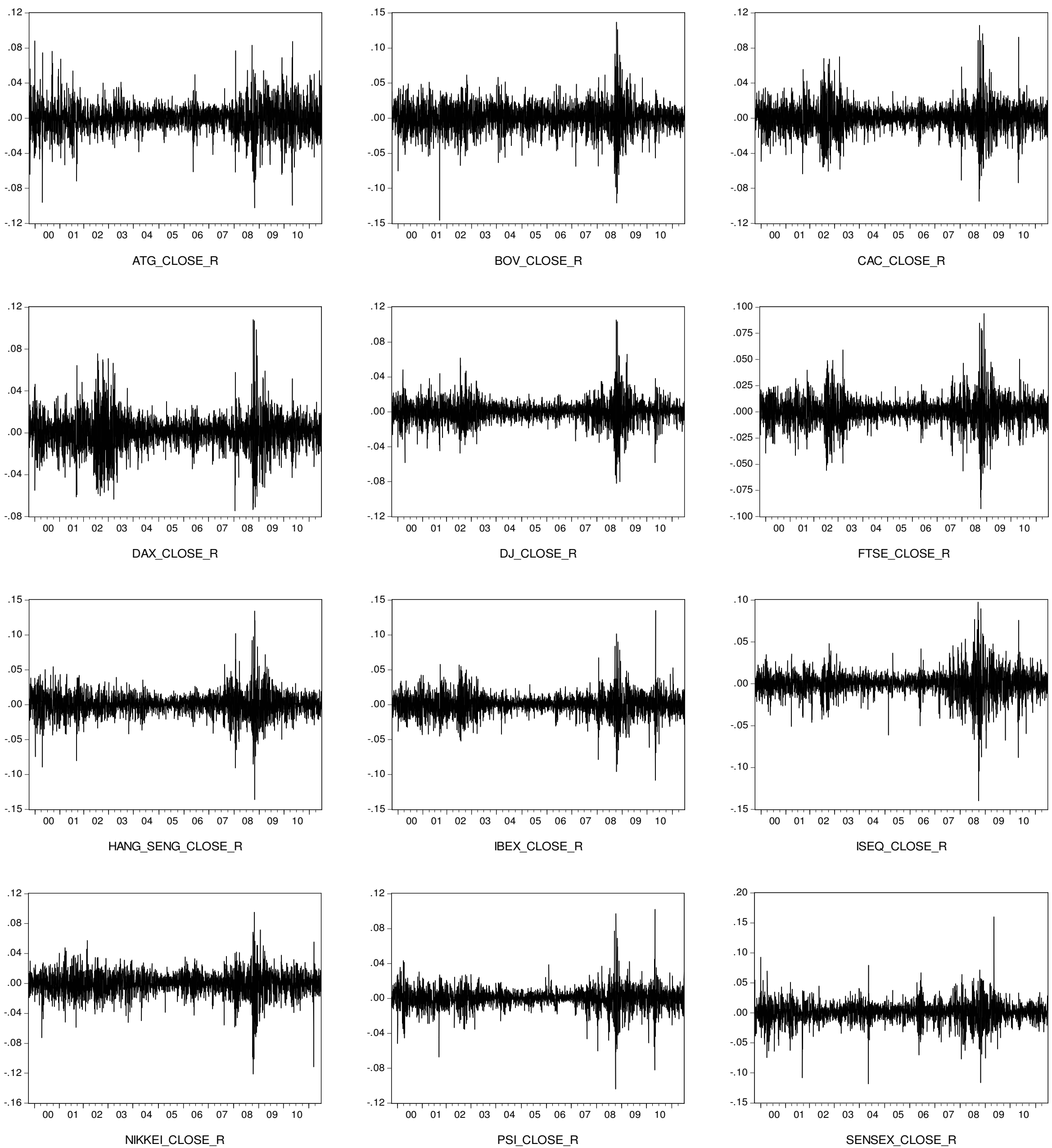


Table 2 presents the descriptive statistics of conditional volatility for the three sub-periods and for the twelve markets, generated by the GARCH (1,1) models. The values shown in Table 2 allow the conclusion that the estimated conditional volatility reveals signs of deviation from normality assumption, taking into account the skewness and kurtosis coefficients. In order to confirm the appropriateness of the adjustment to the normal distribution, in each of the sub-periods and for the twelve series, the Jarque-Bera test was considered. The statistics of this test is given in Table 2. Based on the results, we conclude that all the series are statistically significant at a significance level of 1%, clearly rejecting the hypothesis of normality.

In Dot-Com sub-period, the BOV index showed the highest average conditional volatility, three times higher than ISEQ and PSI indices, as the least volatile markets. For its part, the DAX index showed the greatest degree of variability, measured by the standard deviation.

In the quiet sub-period, Sensex and BOV indices showed higher average of conditional volatility. The remaining markets showed lower levels of volatility. In either case, the recorded values were below those seen during Dot-Com sub-period. Regarding conditional volatility variability, the Sensex index showed the greatest variability. Conversely, DJ and PSI were the least variable.

During global financial crisis sub-period, the differences in volatility levels of various indices were not as pronounced as in the previous sub-periods. HANG-SENG index recorded the highest average conditional volatility, followed by ATG and ISEQ indices. For its part, DJ and PSI indices were the least volatile.

Some estimates are somehow unexpected. This is what happens with the Portuguese market, which has registered the lowest volatility between all the markets, although it is a small developed market, and especially for being under foreign financial assistance since 2011.

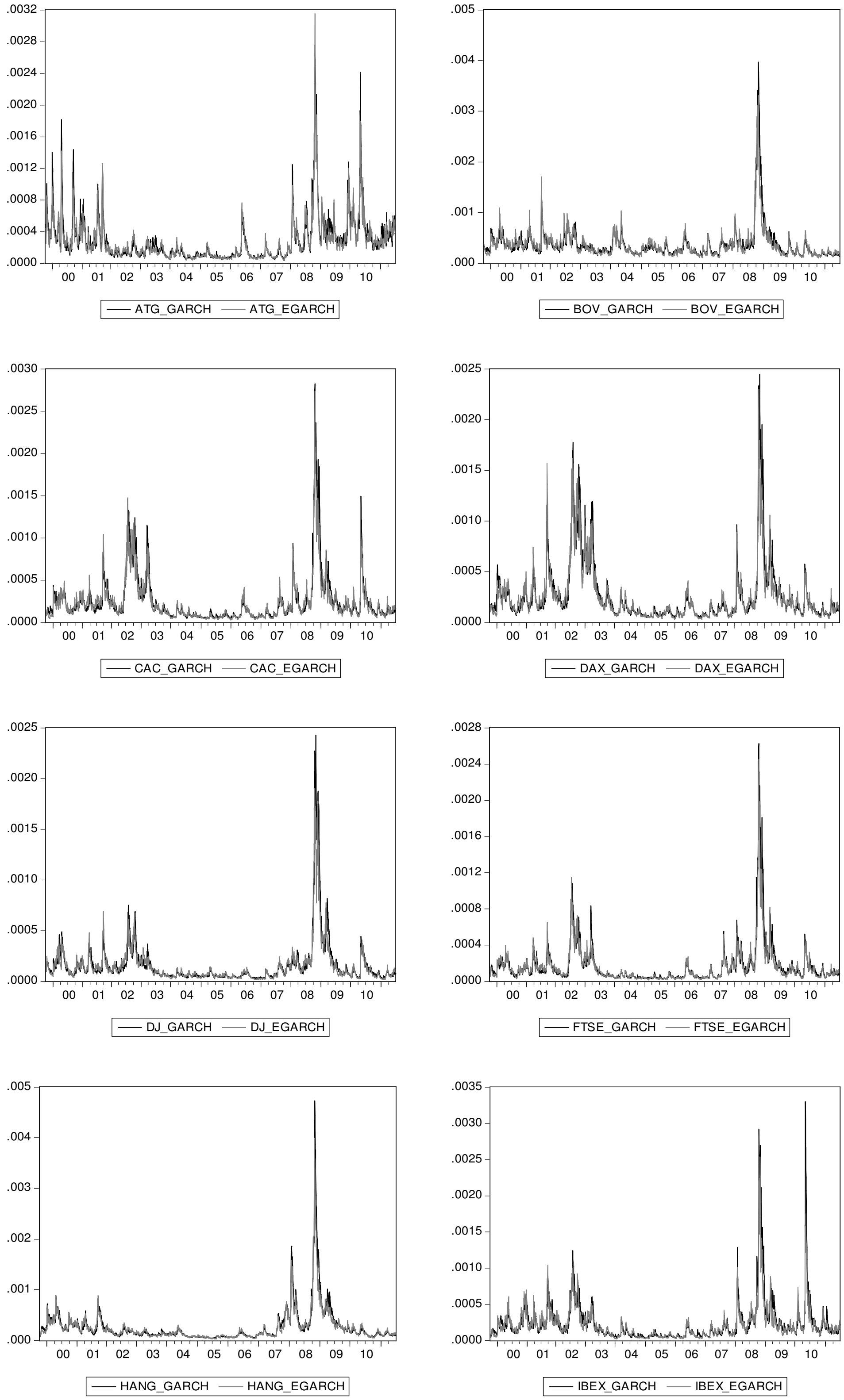
Figure 2 shows the graphical evolution of the conditional volatility of each of the twelve daily indices in the full period, estimated according to GARCH (1,1) and EGARCH (1,1) specifications.

During Dot-Com and global financial crisis sub-periods, the twelve indices recorded higher levels of volatility (see Figure 2). This is related to a set of events that led to a high volatility in the financial markets. In the first sub-period, some relevant market events (as the bursting of the Internet bubble, the terrorist attacks in September 2001 and the accounting scandals at Enron and WorldCom, among others) disrupted markets. In the last sub-period, there was a sequence of events disturbing the environment of financial markets, as the subprime credit crisis and the sovereign debt crisis. In the quiet sub-period, the markets showed more moderate volatility levels, except for the Sensex index.

Table 2. Descriptive statistics from conditional volatility estimates in each sub-period.

		ATG	BOV	CAC	DAX	DJ	FTSE	HANG	IBEX	ISEQ	NIKKEI	PSI	SENSEX
Dot-Com	Mean	0,00032	0,00041	0,00033	0,00039	0,00019	0,00021	0,00026	0,00029	0,00016	0,00023	0,00015	0,00030
	Median	0,00023	0,00036	0,00024	0,00026	0,00015	0,00015	0,00022	0,00024	0,00013	0,00020	0,00011	0,00020
	Maximum	0,00182	0,00159	0,00133	0,00178	0,00075	0,00110	0,00089	0,00124	0,00057	0,00080	0,00088	0,00208
	Minimum	0,00007	0,00018	0,00008	0,00007	0,00004	0,00004	0,00007	0,00005	0,00003	0,00006	0,00001	0,00007
	Std. Dev.	0,00026	0,00016	0,00026	0,00033	0,00012	0,00018	0,00015	0,00018	0,00010	0,00012	0,00012	0,00026
	Skewness	2,18043	2,29706	1,78291	1,62030	1,92477	2,24323	1,28615	1,62711	1,82536	1,48705	2,55613	2,43263
	Kurtosis	8,63930	12,82999	5,46957	5,12411	7,03387	8,58475	4,39739	6,10362	6,29410	5,70628	11,46060	10,83771
	Jarque-Bera	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
Quiet	Mean	0,00013	0,00028	0,00011	0,00014	0,00006	0,00007	0,00010	0,00009	0,00009	0,00015	0,00005	0,00022
	Median	0,00010	0,00025	0,00008	0,00010	0,00005	0,00005	0,00009	0,00007	0,00007	0,00012	0,00004	0,00015
	Maximum	0,00068	0,00079	0,00094	0,00119	0,00029	0,00047	0,00028	0,00054	0,00050	0,00045	0,00024	0,00298
	Minimum	0,00004	0,00014	0,00004	0,00004	0,00003	0,00002	0,00004	0,00004	0,00003	0,00005	0,00002	0,00007
	Std. Dev.	0,00008	0,00010	0,00009	0,00013	0,00003	0,00005	0,00004	0,00006	0,00006	0,00008	0,00003	0,00024
	Skewness	2,95023	1,67660	4,83289	4,22717	2,96002	3,77812	1,15398	2,94617	3,02543	1,32728	1,93437	5,52438
	Kurtosis	14,93283	6,02352	34,30499	26,81288	16,51651	21,96959	4,30542	16,58318	15,40300	4,50041	8,36348	45,45248
	Jarque-Bera	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
G.F.C	Mean	0,00045	0,00044	0,00033	0,00029	0,00024	0,00026	0,00046	0,00036	0,00045	0,00035	0,00024	0,00038
	Median	0,00035	0,00030	0,00019	0,00016	0,00013	0,00014	0,00025	0,00021	0,00028	0,00020	0,00013	0,00023
	Maximum	0,00276	0,00397	0,00283	0,00245	0,00243	0,00263	0,00473	0,00330	0,00400	0,00411	0,00272	0,00383
	Minimum	0,00005	0,00013	0,00007	0,00005	0,00003	0,00004	0,00006	0,00006	0,00005	0,00007	0,00004	0,00007
	Std. Dev.	0,00037	0,00053	0,00040	0,00036	0,00037	0,00036	0,00058	0,00045	0,00052	0,00051	0,00034	0,00041
	Skewness	2,83345	3,79125	3,31273	3,38355	3,45323	3,83869	3,61038	3,42940	3,45159	4,35981	3,98071	3,31030
	Kurtosis	13,07556	18,72910	15,31204	15,52876	15,27991	19,97684	19,47266	16,01513	17,74478	24,08980	21,15388	18,43735
	Jarque-Bera	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)

Figure 2. Evolution of conditional volatility considering GARCH and EGARCH models



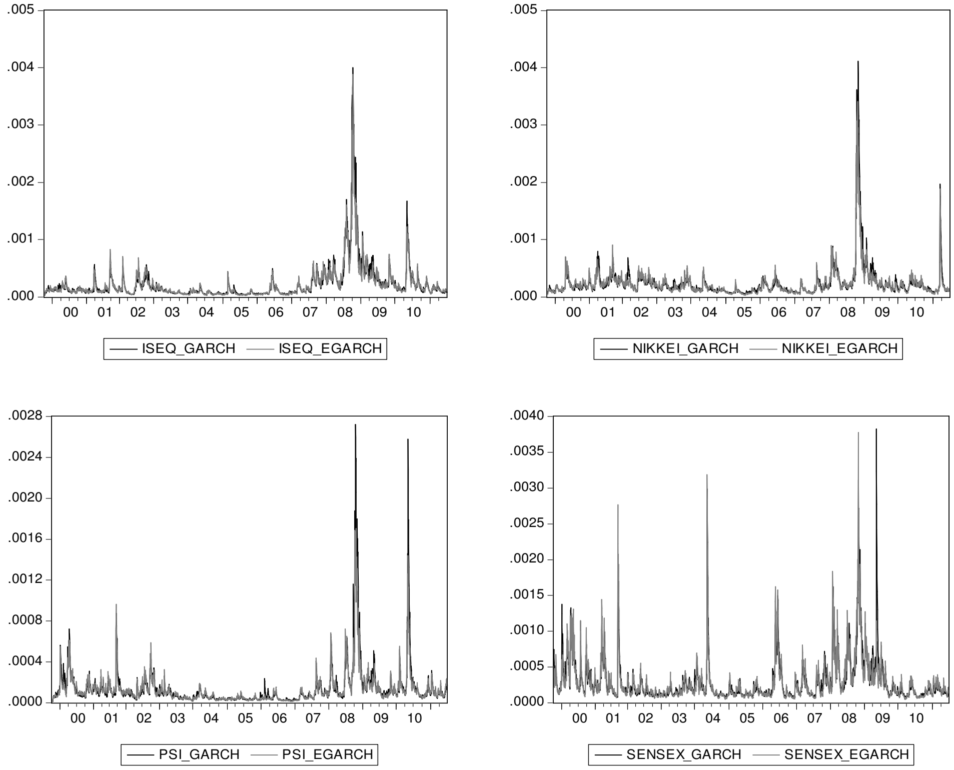


Table 3 presents the GARCH (1,1) estimation results. All the coefficients of the estimated models showed the expected signals, except for β parameter for BOV index during the Dot-Com sub-period, which has a negative coefficient (-0.538). The remaining coefficients are non-negative, ensuring that the conditional variance is positive.

Considering the variance equation coefficients $(\alpha_0, \alpha_1 \text{ and } \beta)$, only the Bovespa coefficients, α_1 and β, in Dot-Com sub-period, are not statistically significant, at a significance level of 10%. Both the DAX coefficient (α_0) in Dot-com sub-period and the HANG-SENG index in Dot-Com and Global Financial Crisis sub-periods, were significant at a significance level of 10%. The remaining coefficients proved to be significant at a significance level of 5%, although most were for the most demanding level (1%). This reveals the existence of ARCH and GARCH effects. Moreover, the sum of GARCH coefficients is less than one for all the indices and for all the sub-periods, whereby the volatility process is stationary.

Table 3. Estimation results for the GARCH (1,1) model

	ATG			BOV			CAC		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
α_0	3,91E-05	3,10E-06	9,32E-06	6,25E-04	1,16E-05	3,64E-06	5,77E-06	2,69E-06	6,54E-06
	(0,000)	(0,002)	(0,024)	(0,001)	(0,020)	(0,003)	(0,028)	(0,000)	(0,004)
α_1	0,229	0,070	0,105	0,038	0,044	0,077	0,072	0,051	0,116
	(0,000)	(0,000)	(0,000)	(0,218)	(0,001)	(0,000)	(0,000)	(0,000)	(0,000)
β	0,642	0,900	0,879	-0,538	0,909	0,913	0,912	0,915	0,866
	(0,000)	(0,000)	(0,000)	(0,206)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
$\alpha_1+\beta$	0,872	0,970	0,984	-0,500	0,953	0,990	0,985	0,966	0,982
	DAX			DJ			FTSE		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
α_0	5,25E-06	2,75E-06	4,11E-06	1,13E-05	1,80E-06	2,36E-06	5,04E-06	2,27E-06	3,32E-06
	(0,051)	(0,001)	(0,002)	(0,010)	(0,007)	(0,000)	(0,006)	(0,002)	(0,011)
α_1	0,093	0,063	0,101	0,105	0,031	0,103	0,122	0,075	0,102
	(0,000)	(0,000)	(0,000)	(0,000)	(0,004)	(0,000)	(0,000)	(0,000)	(0,000)
β	0,897	0,909	0,885	0,837	0,929	0,887	0,856	0,880	0,885
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
$\alpha_1+\beta$	0,990	0,971	0,986	0,942	0,960	0,991	0,979	0,955	0,987
	HANG-SENG			IBEX			ISEQ		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
α_0	5,74E-06	8,18E-07	2,81E-06	7,57E-06	5,28E-06	1,03E-05	1,58E-05	3,39E-06	5,89E-06
	(0,018)	(0,052)	(0,070)	(0,045)	(0,000)	(0,001)	(0,001)	(0,000)	(0,009)
α_1	0,068	0,027	0,101	0,074	0,086	0,134	0,112	0,078	0,120
	(0,000)	(0,000)	(0,000)	(0,001)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
β	0,913	0,963	0,893	0,901	0,839	0,841	0,782	0,880	0,870
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
$\alpha_1+\beta$	0,981	0,991	0,995	0,975	0,925	0,975	0,895	0,958	0,991
	NIKKEI			PSI			SENSEX		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
α_0	1,26E-05	2,11E-06	1,04E-05	1,98E-05	1,17E-06	8,00E-06	1,92E-05	1,14E-05	2,47E-06
	(0,020)	(0,002)	(0,001)	(0,000)	(0,001)	(0,000)	(0,000)	(0,000)	(0,017)
α_1	0,076	0,062	0,154	0,170	0,047	0,169	0,147	0,150	0,102
	(0,002)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
β	0,872	0,922	0,817	0,697	0,922	0,802	0,789	0,790	0,897
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
$\alpha_1+\beta$	0,948	0,984	0,971	0,867	0,969	0,971	0,936	0,940	0,999

Note: This table presents the GARCH (1.1) model estimations, applied to daily returns of the twelve indices studied in the three sub-periods. All estimates are based on Maximum Likelihood estimation.

In order to test autocorrelation, the Box-Ljung test (see Table 4) was applied. The results indicate that, for a significance level of 5%, there is a strong evidence of accepting the null hypothesis, concluding that the standardized residues are not correlated. In all the cases, the Ljung-Box test results reveal that the p-values are above the significance level of 5%.

Table 4. Ljung-Box and LM tests results to GARCH (1,1) residuals

	ATG			**BOV**			**CAC**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	13,391	25,559	11,658	86,305	15,655	12,176	20,705	17,531	18,058
	(0,860)	(0,181)	(0,927)	(0,987)	(0,738)	(0,910)	(0,415)	(0,618)	(0,584)
LM test: $F_{(20)}$	0,640	1,189	0,645	8,128	14,509	0,629	0,951	0,826	0,901
	(0,884)	(0,255)	(0,881)	(0,991)	(0,804)	(0,894)	(0,521)	(0,683)	(0,586)
	DAX			**DJ**			**FTSE**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	18,607	20,775	12,930	12,352	14,081	16,324	9,832	25,698	17,846
	(0,547)	(0,410)	(0,880)	(0,903)	(0,826)	(0,696)	(0,971)	(0,176)	(0,598)
LM test: $F_{(20)}$	0,816	1,007	0,640	0,631	0,721	0,786	0,497	1,323	0,879
	(0,695)	(0,451)	(0,884)	(0,892)	(0,807)	(0,732)	(0,968)	(0,154)	(0,614)
	HANG-SENG			**IBEX**			**ISEQ**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	10,969	27,791	21,839	25,389	13,158	21,832	18,161	14,735	16,532
	(0,947)	(0,114)	(0,349)	(0,187)	(0,871)	(0,350)	(0,577)	(0,791)	(0,683)
LM test: $F_{(20)}$	0,532	1,383	1,081	1,211	0,633	1,153	0,988	0,696	0,820
	(0,954)	(0,121)	(0,364)	(0,237)	(0,891)	(0,289)	(0,474)	(0,833)	0,690)
	NIKKEI			**PSI**			**SENSEX**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	22,021	17,577	16,394	15,693	10,493	22,770	19,104	13,967	68,843
	(0,339)	(0,615)	(0,692)	(0,735)	(0,958)	(0,300)	(0,515)	(0,832)	(0,997)
LM test: $F_{(20)}$	1,085	0,807	0,914	0,746	0,500	1,089	1,186	0,735	0,336
	(0,360)	(0,707)	(0,570)	(0,780)	(0,967)	(0,355)	(0,259)	(0,792)	(0,997)

Note: This table presents the results of Ljung-Box and ARCH LM tests, for the residuals from GARCH (1,1) estimation, for the three sub-periods, and considering the lag 20. Values between parentheses show probability values for each test.

To verify the variance persistence, the ARCH-LM test was applied. The results are shown in Table 4. The analysis of the coefficients and its respective probability values indicates that they are not statistically different from zero. Testing coefficients in the group, the probability (F-statistic) is significant, so the null hypothesis is accepted. There is reason to believe that estimated models have the ability to model conditional heteroskedasticity.

Sensitivity and Persistence

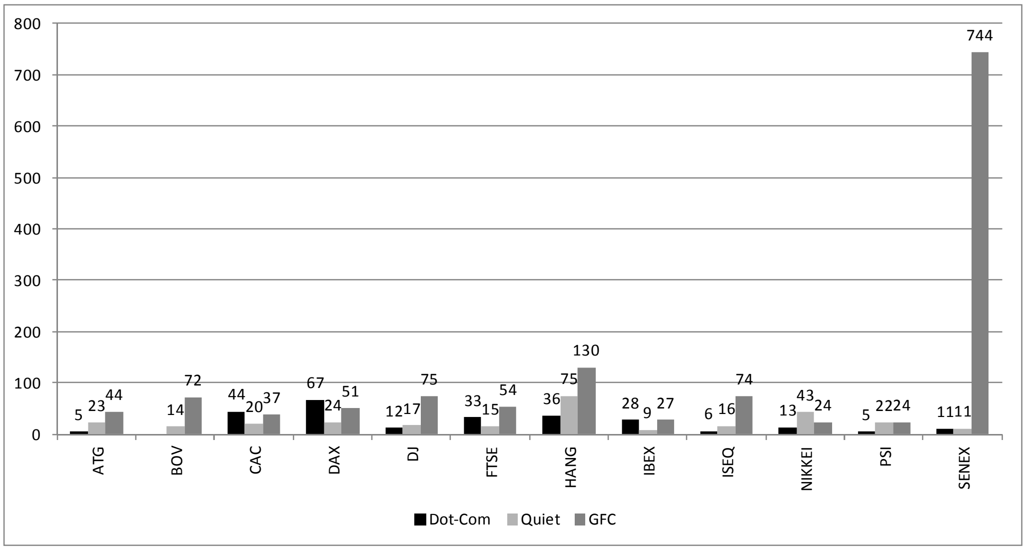
During the global financial crisis, the estimated coefficients of the GARCH (1,1) model were above 0.1, with the exception of the Bovespa index. So the volatility in this sub-period was highly sensitive to market events. The increase in sensitivity was particularly significant in HANG-SENG (269%), PSI (258%) and DJ (234%) indices. The results during the global financial crisis contrasts with the Dot-Com sub-period, in which only five indices were above 0.1. In the quiet sub-period, only the SENSEX index described such superiority. This allows the conclusion that, during the global financial crisis sub-period, stock markets were more sensitive than in the preceding sub-periods.

In the GARCH model, volatility persistence is measured summing α_1 and β parameters. When this sum is close to the unit, there is a strong indication of persistence or long memory. Table 3 shows the values of volatility persistence for each index in each sub-period, calculated on the basis of GARCH estimates. These results show that in the quiet sub-period, when compared to the preceding ones, persistence increased in eight of the twelve indices; while in the global financial crisis sub-period, in comparison to the preceding ones, the increase did not happen with the exception of the case of NIKKEI index.

The estimated coefficients of the GARCH (1,1) model also allow to conclude about stationary covariance. In all the cases, the sum of α_1 and β coefficients is less than one. According to Alexander (2008), this sum determines the rate of convergence of conditional volatility for the long-term average level. When the sum of these coefficients is relatively high (above 0.99), the volatility term structure is relatively flat. During the global financial crisis sub-period, this superiority was found in the BOV, DJ, HANG, ISEQ and SENSEX indices. For the preceding sub-periods, only the HANG-SENG index, in the second sub-period, verified this superiority.

Figure 3 shows the results of the half-life measure. As we have concluded above, only the NIKKEI index was not more persistent in the global financial crisis sub-period.

Figure 3. Half-life estimates in the three sub-periods



The results also indicate that, during the three sub-periods, the volatility of daily returns proved to be quite persistent, especially in the last sub-period. Half-life was particularly high in HANG-SENG (130) and SENSEX (744) indices. In this sub-period, NIKKEI and PSI indices had recorded the lowest half-life, with a value of 24. In both cases, an unanticipated shock in the daily returns produces, on average, effects on volatility for 24 days.

Tests for equality of means and variances

A visual analysis of Figure 2 leads to a first conclusion: Dot-Com and Global Financial Crisis sub-periods were characterized by a higher concentration of volatility and showed peaks of volatility. The quiet sub-period reveals that volatility levels were much lower than that in the other two sub-periods. The Sensex index was the exception, which showed peaks of volatility in the quiet sub-period.

For a more detailed conclusion, we examined the tests for equality of means and for equal variances between the global financial crisis sub-period and the two preceded sub-periods (see Table 5).

Table 5. Mean and variance equality tests and their p-values

	GFC/Dot-Com				GFC/Quiet			
	Mean Equality		Variance Equality		Mean Equality		Variance Equality	
	t-test	ANOVA	F-test	Bartlett	t-test	ANOVA	F-test	Bartlett
ATG	3,672	13,482	2175,525	6071,184	27,731	768,997	19,545	1783,981
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
BOV	1,794	3,218	11,165	1039,594	9,810	96,239	26,388	2078,178
	(0,073)	(0,073)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
CAC	0,823	0,033	2,431	169,574	17,503	306,358	18,741	1743,510
	(0,855)	(0,855)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
DAX	-6,571	43,184	1,183	6,361	12,745	162,430	7,937	969,367
	(0,000)	(0,000)	(0,011)	(0,012)	(0,000)	(0,000)	(0,000)	(0,000)
DJ	4,143	17,168	9,124	897,986	16,326	266,554	147,403	3859,426
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
FTSE	4,014	16,112	3,986	390,601	17,811	317,231	47,292	2668,864
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
HANG-SENG	9,329	87,029	15,696	1289,555	19,722	388,975	178,092	4060,199
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
IBEX	4,211	17,732	6,033	627,222	19,610	384,561	60,734	2927,508
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
ISEQ	15,872	251,928	26,860	1704,144	22,554	508,674	85,414	3283,633
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
NIKKEI	6,710	45,023	18,327	1406,947	13,242	175,355	46,231	2645,536
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
PSI	7,135	50,909	8,753	869,533	17,903	320,535	147,359	3859,112
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
SENSEX	4,802	23,058	2,423	168,393	10,716	114,840	2,840	270,776
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)

Note: Values between parentheses show probability values.

The results shown in Table 5 allow several conclusions. Comparing global financial crisis and Dot-Com sub-periods, we conclude that the average conditional volatility indicates statistical differences, at a significance level of 1%, with the exception of the BOV, CAC and DAX indices. The BOV index showed a statistical difference at a significance level of 10%. The CAC index revealed no statistical difference, whereas the DAX index showed a decreasing average of conditional volatility, at a significance level of 1%. Additionally, the test of equality of variances, applied to the conditional volatilities comparing the first and the third sub-periods, supports the conclusion that all the reported indices increase, at a significance level of 5%.

The comparison of the last sub-periods allows the conclusion that all the daily average volatilities recorded strong increases, with statistical significance at a significance level of 1%. In some cases, increases were greater than 300%. This happened with the ISEQ (409%), PSI (362%), Hang-Seng (338%) and DJ (303%) index. The Brazilian market increased by 58%. Moreover, increases on average volatility were complemented by increases in variability and evidenced by testing the equality of variances, which in all the cases were significant at a significance level of 1%. The results indicate the occurrence of a generalized increase in conditional volatility. This increase was not restricted to the U.S. market (which led to the subprime crisis) or the euro area markets (in the epicenter of the sovereign debt crisis), revealing a global scale.

Asymmetric effect

To analyze the asymmetric effect, EGARCH (1.1) models were estimated, from the returns of the twelve indices. The estimated results are shown in Table 6.

Table 6. Estimation results for the EGARCH (1,1) model.

	ATG			**BOV**			**CAC**		
	Dot-Com	*Quiet*	*GFC*	*Dot-Com*	*Quiet*	*GFC*	*Dot-Com*	*Quiet*	*GFC*
α_0	-1,151	-0,455	-0,378	-1,063	-2,020	-0,221	-0,301	-0,332	-0,375
	(0,000)	(0,000)	(0,000)	(0,014)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
α_1	0,341	0,154	0,165	0,114	0,027	0,146	0,137	0,068	0,139
	(0,000)	(0,000)	(0,000)	(0,036)	(0,474)	(0,000)	(0,000)	(0,001)	(0,000)
γ	-0,100	-0,044	-0,079	-0,074	-0,238	-0,090	-0,055	-0,129	-0,194
	(0,000)	(0,001)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
β	0,894	0,963	0,969	0,875	0,758	0,987	0,977	0,970	0,969
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
	DAX			**DJ**			**FTSE**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
α_0	-0,372	-0,338	-0,327	-0,239	-0,579	-0,349	-0,306	-0,365	-0,291
	(0,000)	(0,000)	(0,000)	(0,002)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
α_1	0,187	0,103	0,142	0,056	0,075	0,142	0,139	0,072	0,114
	(0,000)	(0,000)	(0,000)	(0,035)	(0,001)	(0,000)	(0,000)	(0,004)	(0,000)
γ	-0,049	-0,111	-0,155	-0,112	-0,107	-0,147	-0,094	-0,125	-0,149
	(0,002)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
β	0,972	0,971	0,975	0,978	0,947	0,973	0,978	0,968	0,977
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
	HANG-SENG			**IBEX**			**ISEQ**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
α_0	-0,290	-0,192	-0,259	-0,335	-1,039	-0,333	-0,734	-0,968	-0,349
	(0,001)	(0,006)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
α_1	0,147	0,072	0,178	0,109	0,138	0,147	0,120	0,134	0,221
	(0,000)	(0,000)	(0,000)	(0,003)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
γ	-0,060	-0,018	-0,066	-0,085	-0,160	-0,162	-0,124	-0,135	-0,071
	(0,000)	(0,040)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
β	0,979	0,985	0,985	0,970	0,902	0,974	0,928	0,908	0,978
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
	NIKKEI			**PSI**			**SENSEX**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
α_0	-0,560	-0,502	-0,426	-1,293	-0,489	-0,558	-0,981	-1,229	-0,308
	0,002	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
α_1	0,146	0,171	0,196	0,268	0,118	0,225	0,284	0,274	0,220
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
γ	-0,055	-0,078	-0,126	-0,108	-0,005	-0,134	-0,125	-0,172	-0,074
	(0,009)	(0,000)	(0,000)	(0,000)	0,735	(0,000)	(0,000)	(0,000)	(0,000)
β	0,947	0,959	0,968	0,880	0,961	0,957	0,908	0,882	0,983
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)

Notes: This table presents the EGARCH (1,1) model estimations, applied to the daily returns of the twelve indices studied in the three sub-periods. All the estimates are based on Maximum Likelihood.

Estimates show that all the γ coefficients had a negative sign. Additionally, in the three sub-periods, these coefficients were statistically different from zero, at a significance level of 1%. The exceptions were the HANG-SENG index in the quiet sub-period, which was statistically significant at a significance level of 5%, and the PSI index in the quiet sub-period, where asymmetry coefficient was not proved to be statistically different from zero. The high significance of the asymmetry coefficient clearly shows the existence of asymmetric shocks in the volatility process. In this sense, one can conclude that in the three sub-periods, "bad news" was more impactful than "good news".

A comparison of the asymmetry coefficients in the three sub-periods, allows the conclusion that a rising trend of these values has been verified. From the first to the second sub-period, eight indices reported an increase in the asymmetry coefficient (in absolute value). From the second to the third sub-period, there was an increase in nine asymmetry coefficients. When comparing the first and the third sub-periods, the same happens in nine markets. The results showed that markets are, in general, more sensitive to "bad news" than to "good news", especially during the global financial crisis.

To find the correct EGARCH (1,1) model specifications, we examined the residuals in order to see whether they exhibit a white noise process. For this purpose, we turn to the Ljung-Box and ARCH-LM tests (see Table 7).

Table 7. Ljung-Box and LM tests results for EGARCH (1,1) residuals

	ATG			**BOV**			**CAC**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	19,919	27,742	16,072	7,089	34,510	15,572	19,803	17,643	27,472
	(0,463)	(0,116)	(0,712)	(0,996)	(0,023)	(0,743)	(0,470)	(0,611)	(0,123)
LM test: $F_{(20)}$	0,900	1,324	0,854	0,333	1,568	0,763	0,960	0,766	1,403
	(0,588)	(0,154)	(0,647)	(0,998)	(0,053)	(0,760)	(0,510)	(0,757)	(0,112)
	DAX			**DJ**			**FTSE**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	38,165	21,030	28,201	16,185	15,783	22,664	12,745	21,298	19,660
	(0,008)	(0,395)	(0,105)	(0,705)	(0,730)	(0,306)	(0,888)	(0,380)	(0,479)
LM test: $F_{(20)}$	1,863	0,988	1,298	0,858	0,836	1,057	0,679	0,984	0,993
	(0,012)	(0,474)	(0,171)	(0,643)	(0,670)	(0,391)	(0,850)	(0,479)	(0,468)
	HANG-SENG			**IBEX**			**ISEQ**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	17,277	34,011	30,617	25,913	15,817	23,266	18,589	20,291	17,008
	(0,635)	(0,026)	(0,060)	(0,169)	(0,728)	(0,276)	(0,549)	(0,440)	(0,652)
LM test: $F_{(20)}$	0,940	1,654	1,487	1,230	0,735	1,291	0,997	0,947	0,870
	(0,536)	(0,035)	(0,077)	(0,221)	(0,793)	(0,176)	(0,463)	(0,526)	(0,627)
	NIKKEI			**PSI**			**SENSEX**		
	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC	Dot-Com	Quiet	GFC
LB: $Q^2_{(20)}$	23,864	22,003	15,676	16,231	13,262	18,912	16,177	20,286	8,521
	(0,248)	(0,340)	(0,737)	(0,702)	(0,866)	(0,528)	(0,706)	(0,440)	(0,988)
LM test: $F_{(20)}$	1,221	1,006	0,837	0,777	0,632	0,938	0,935	1,024	0,396
	(0,229)	(0,452)	(0,669)	(0,744)	(0,891)	(0,538)	(0,542)	(0,430)	(0,992)

Notes: Table 7 presents the Ljung-Box and ARCH LM tests for the residuals from the GARCH (1,1) estimation for the three sub-periods, and considering the lag 20. Values between parentheses show probability values for each test.

The Ljung-Box test does not accept the null hypothesis for BOV (quiet sub-period), DAX (Dot-Com sub-period) and HANG-SENG (quiet sub-period) indices at the significance level of 5%. For the remaining indices, there is a strong evidence of acceptance of the null hypothesis, concluding that the standardized residues are not correlated because the results of the test showed that the p-value is very above the significance level of 5%. The LM test results (see Table 7) confirmed the previous conclusions. The group test (F-Statistic) showed that the probability is not significant in the cases mentioned above, rejecting the null hypothesis.

4. SUMMARY, CONCLUSIONS AND LIMITATIONS

In this work, we have studied the current financial crisis. According to several authors, this crisis is the most severe after the Great Depression and the first global financial crisis the world has known.

To analyze the crisis, various stock markets were considered, which all together represent about 62% of the world stock market capitalization, in order to understand the impact of global financial crisis on the level of volatility, sensitivity, persistence and asymmetric effect. For this purpose, we studied the period from October 4th 1999 to June 30th 2011, which was divided into three sub-periods: One corresponding to the Dot-Com crisis; other relative to a phase of rise and accumulation for global indices; and finally, one corresponding to the global financial crisis. To estimate the market volatility, generalized and exponential autoregressive conditional heteroskedasticity models were considered.

The findings confirm that, in most cases, the conditional volatility in the global financial crisis sub-period experienced a significant increase compared with the previous two sub-periods, but particularly in relation to the quiet sub-period. Note that the PSI index showed, in all sub-periods analyzed, lower levels of conditional volatility, which is somehow surprising if we take into account the small size of this market. Additionally, the model estimation confirms, in general, a higher persistence in volatility during the financial crisis sub-period; it is the same with sensitivity. Similarly, all the markets considered in the analysis revealed an asymmetric effect; in other words, their volatilities were more influenced by "bad news" than by "good news", especially during the global financial crisis.

Several limitations of our analysis should be noted. First, the sample period covers only the first years of the global financial crisis, but financial markets are suffering with this crisis because it has not finished yet. Second, this study considered only twelve stock markets, including some major capitalizations and markets directly related to sovereign debt crisis. For more robust conclusions, future work may cover the full period of the global financial crisis and consider a large set of developed and emerging markets.

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